Develop Hybrid Architecture for Brain Tumor Identification

Synopsis of the Research Proposal

Submitted for the Registration in the

Ph.D. Program (Part-Time) in Engineering

By

SONAM JAIN

24RDCDIUJDD02021

Under Supervision of

Dr. Mukesh Kalla

Associate Professor

THE ICFAI UNIVERSITY JAIPUR

LIST OF CONTENTS

ABSTRACT 3

1. INTRODUCTION 4
2. LITERATURE REVIEW 10
3. RESEARCH GAP 24
4. RESEARCH OBJECTIVES 25
5. RESEARCH METHODOLOGY 26
6. WORKPLAN OF RESEARCH 29
7. REFERENCES 30

ABSTRACT

Brain tumors require accurate diagnosis for effective treatment. Traditional MRI analysis is time-consuming and subjective. While deep learning shows potential in brain tumour classification, existing approaches face challenges including limited accuracy, computational complexity, and poor generalization. This research proposes a novel Hybrid Deep Learning Model combining Convolutional Neural Networks (CNNs), Vision Transformers, and attention mechanisms. The framework leverages transfer learning from pre-trained models (ResNet, EfficientNet, VGG, Xception) with custom fusion layers for multi-scale feature extraction. The methodology encompasses three objectives enhanced preprocessing with intensity normalization and data augmentation; multi-branch hybrid architecture combining CNN-based extractors with transformer attention modules; and ensemble learning with meta-heuristic optimization (Genetic Algorithms, Particle Swarm Optimization, Whale Optimization). The model performs multi-class classification of glioma, meningioma, pituitary tumors, and normal tissues. Unlike conventional approaches, the hybrid model exploits complementary feature representations, enhancing discriminative capability. Attention mechanisms identify tumour-specific features while mitigating artifacts. Ensemble voting reduces overfitting and improves robustness. Experimentation on Kaggle, BraTS and Figshare, and datasets will validate performance using accuracy, precision, recall, F1-score, and AUC-ROC metrics. Grad-CAM visualization enhances interpretability for clinical acceptance. Expected outcomes include greater accuracy, reduced computational overhead, and a scalable clinical decision support system for improved patient outcomes.

1. INTRODUCTION

Brain tumors are a dangerous type of cancer that poses a significant threat to the lives of those who have them and affects a substantial number of individuals worldwide. In order to appropriately plan for therapy, keep track of how the condition develops, and categorize and locate any tumors that may be present, it is imperative that brain tumors be correctly identified [1]. Because of the fact that the instruments used for diagnosis are not capable of providing an accurate measurement of the tumor, the initial phases of brain tumor diagnosis are widely regarded as being extremely difficult [2]. On the other hand, the prognosis for the patient's survival and recovery can be improved if doctors start the necessary treatment as soon as the brain tumor is discovered. The treatment options that may be considered, depending on the nature of the tumor, include chemotherapy, radiation therapy, and surgery The diagnosis of brain tumors can be quite difficult to make due to the fact that the forms, sizes, locations, and appearances of these tumors can vary so greatly from one patient to another. The dependability of the architecture is contingent upon the quality of the results and the clarity of the visualization. The method of medical imaging that is employed in the diagnosis of cancer is important in the resolution of diagnostic problems. Magnetic Resonance Imaging (MRI) has lately acquired favor as a robust imaging method for assessing brain tumors due to its capacity to provide particular structural information [4].A complex DNN is a type of black box that obscures both the reasons behind and the processes via which a model makes.In recent years, there has been a great deal of progress anda greater utilization of Convolution Neural Networks (CNNs), especially when it comes to making decisions [5].

The following examples illustrate three separate detections (one for each model) on the magnetic resonance imaging scans of three distinct patients.A label that is positioned above the bounding box indicates the class of the detection (either "tumor" or "not tumor"), and a confidence score (with a minimum of 0 and a maximum of 1) is presented to the side of the label.

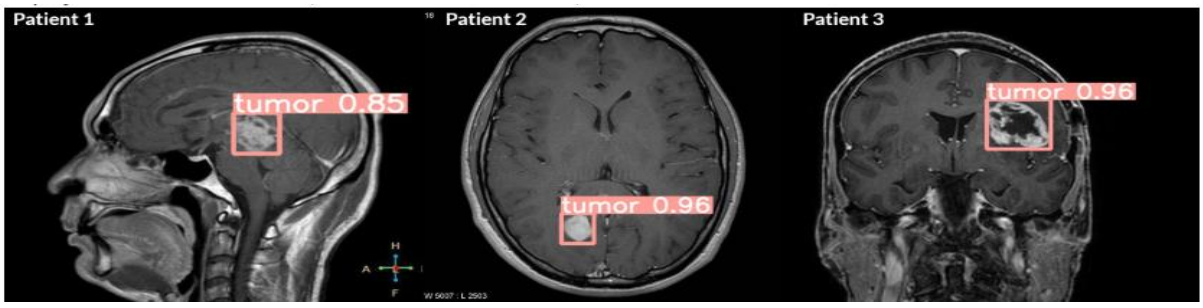

Figure 1:Example of brain tumor

Types of Brain Tumors:

a. **Primary Tumors:** Originate within the brain.
   - **Gliomas:** Ependymomas, oligodendrogliomas, and astrocytoma should all be on the list.
   - **Meningiomas:**Upon emerging from the meninges, the fatty sheaths that encase the central nervous system.
   - **Pituitary Adenomas:** Take a look at the pituitary gland.

b. **Medulloblastomas:** Happen in the brain and are common in kids.

c. **Secondary (Metastatic) Tumors:**Originate elsewhere in the body and spread to the brain.

d. **Classification: By Grade (WHO Classification):**
   - Grade I: Slow-growing, non-invasive.
   - Grade II: Relatively slow-growing, may invade adjacent tissue.
   - Grade III: Malignant, invasive, faster growth.
   - Grade IV: Highly malignant, aggressive (e.g., glioblastoma).

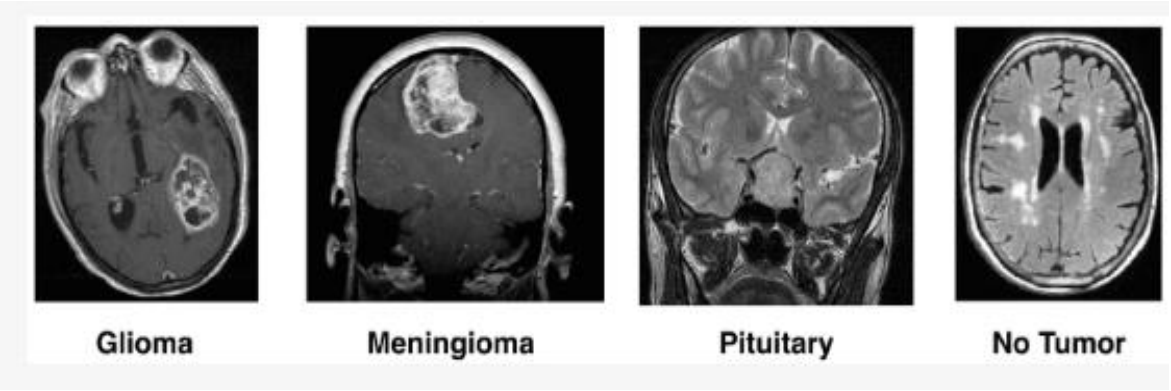

Figure 2:Four(4) types of MRI images of brain tumor.

Background

Brain tumor detection has undergone a significant transformation over the past decades, evolving from conventional radiological practices to advanced artificial intelligence–driven techniques. Traditionally, diagnosis relied heavily on manual interpretation of MRI and CT scans by radiologists, who assessed tumor shape, location, and intensity variations. Although effective, this traditional approach was time-consuming, subjective, and highly dependent on the experience of the clinician, often leading to variability in results. The introduction of Artificial Intelligence (AI) marked the first major shift, enabling computer-based systems to support radiologists by enhancing image quality, highlighting suspicious regions, and reducing human error. As AI progressed, Machine Learning (ML) techniques such as Support Vector

Machines, Random Forests, and k-Nearest Neighbors became popular for tumor classification. These methods extracted handcrafted features (texture, edges, intensity patterns) and used them for automated detection. While ML improved accuracy, it still depended on the quality of manually engineered features. The emergence of Deep Learning (DL) — especially Convolutional Neural Networks (CNNs) — revolutionized brain tumor detection by enabling end-to-end learning, where the model automatically extracts features directly from raw images. DL methods significantly outperform traditional and ML approaches by providing higher accuracy, better generalization, and robust tumor segmentation without relying on manual feature engineering. Overall, the progression from traditional diagnosis to AI, ML, and DL represents a continuous effort to achieve faster, more accurate, and more consistent detection of brain tumors [3].

Deep Learning

The field of deep learning has made significant progress in the past few years, and this progress may potentially relieve these issues by automating the process of identifying brain tumors through the use of the MRI image dataset. The performance of CNNs in picture categorization tasks has been shown to be outstanding. Consider CNNs like EfficientNet, MobileNetV2, VGG-19, VGG-16, and many more. Intricate patterns and qualities can be found and classified using prior datasets by these algorithms, allowing them to differentiate between various brain tumor types. Using deep learning for medical imaging could significantly improve diagnostic accuracy and consistency while drastically cutting down on diagnostic time and effort [4].

Brain Tumor Statistics

Brain and spinal cord make up the brain and the rest of the vertebrates.The brain not only controls many bodily functions, but it also thinks, plans, decides, and tells the body what to do. How the brain is put together is very complicated.Some Computer Numerical Control (CNC)problems, like headaches, strokes, infections, and brain tumors, can be hard to find, study, and treat [5].

Brain tumors are growths of brain cells that are not working normally in the head [6,7]. It might be tough to grow something in a little place. It's very dangerous because any growth in the brain can hurt it [8,9]. Brain tumors kill tenth of all people who die, whether they are kids or adults [10]. Different types of tumors have low life rates that depend on how they look, where they are located, and how they are made [11,12]. There are 700,000 people with brain

tumors; 80% of them are healthy and 20% are dangerous [13]. In 2021, the American Cancer Society found brain tumors in 78,980 people, with 24,530 being cancerous and 55,150 not being cancerous [14]. There were 13,840 men and 10,690 women among them. Research [15] shows that brain tumors are the main reason people and children around the world die from cancer.

Digital medical pictures help doctors figure out what's wrong with a lot of people. They can also be used for other things, like training, education, and study. More and more, medical things need to be photographed digitally. Between 12,000 and 15,000 shots were taken every day at the University Hospital of Geneva in 2002 [16]. It is important to have a solid computer-aided diagnostic system for medical reports and imaging studies. Medical age evaluations that are done by hand are slow, not always accurate, and prone to mistakes. [17]. A lot of medical tests and treatments use machine learning and deep learning. Several algorithms have been tried and found to be very good at finding brain tumors and putting them into groups [18].There are CNN models like GoogLeNet, AlexNet, and ResNet-34 that have already been trained on medical pictures and are used by Deep Learning (DL) to put brain tumors into groups [19].DL uses deep neural networks that have a lot of levels. [20–21]

Symptoms

Neurological problems caused by a brain tumor will be different based on where it is because different parts of the brain control different functions. A cerebellum growth near the back of the head, for instance, could make it hard to move, walk, balance, and coordinate your movements. In the event that the tumor impacts the optic system responsible for seeing, visual problems may occur. A brain tumor's most common signs may include:

- Headaches
- Seizure or convulsion
- Trouble thinking, speaking, or remembering words;
- Changes in personality or behavior;
- Weakness, stiffness, or paralysis in one body part or side;
- Dizziness, losing equilibrium, or feeling unsteady
- Changing vision and hearing loss.
- Disorientation and confusion.
- Losing memories

Risk Factors

Family history: Only 5-10% of malignancies are genetically inherited. Genetic counseling is suggested if there is a family history of brain tumors.

● Age: The risk of most forms of brain tumors rises with age.

● Chemical exposure: There is mounting evidence that exposure to some chemicals, including those found in the workplace, can raise the risk of brain cancer.

● Radiation exposure: Ionizing radiation from high-radiation cancer therapy and nuclear fallout can raise the risk.[21]

Motivation

Cancer is a life-threatening sickness and it is also evident that if the early treatment is offer to the patient with the right combination of the therapy, then the chances of the survival of the patient is increase. During the last one decade lots of research has been produced and investigated, number of researchers have developed new techniques to segment, detect and classify tumor types using the modern techniques based on SVM, SOM, FCM and GA, Principal Component Analysis (PCA) etc. In spite of many researches has developed to detect tumor from the MRI or from other modern imaging modalities, no researches are fully automatic and adoptable. In addition, no research has been conducted to generate automatic reports. This may be the first attempt to study an automatic report generation scheme integrated to promotion radiologists or clinical supervisors in conducting rapid diagnostic analysis. In order to construct a comprehensive medical imaging folder, this study aims to extract pertinent data from segmented tumor regions or classify tumor tissues as healthy or infectious. The results of this study help to quickly and accurately classify benign and malignant tumors, thereby improving the diagnosis of tumor sections. From the literature discovery, we are motivated to solve the following problems by MRI Brain Image Segmentation (Level Set Method with Gradient-Based Watershed Turnaround) and deep learning-based feature extraction and SVM based classification.

Society Significance

The study of brain tumors is very important for society because it helps solve big problems in the business, public health, and mental health. More people survive, healthcare costs go down, and patients have a better quality of life when they get a diagnosis early, try new treatments, and spread the word. Finding out more about brain tumors does more than just help treat

them. It does this by pushing for progress in technology in areas like medical images and artificial intelligence (AI). People in a community can spot signs earlier when they know more about them. This lets helpers act quickly and reduces stigma. Treatments that work also make people more productive at work and help them work together around the world. This makes healthcare fairer and leads to better policies and treatments.Working together not only saves lives but also makes society stronger against serious illnesses.

2. LITERATURE REVIEW

This literature review examines significant contributions of research from 2020 to 2025, highlighting the evolution of deep learning techniques, their clinical applications, and the ongoing efforts to develop robust, interpretable, and scalable brain tumor detection systems. The following studies provide a comprehensive overview of methodologies, performance metrics, and future directions in this rapidly advancing field.

S. Aksoy et.al. (2025) This study proposed several preprocessing methods to get the MRI images ready that were used to train the model. By utilizing a low dilation rate (2,1,1) for the global path and a high dilation rate (4,2,1) for decreasing even numbers, gridding effects may be eliminated and coarse and fine characteristics can be recovered from the two parallel courses.This dilated PDCNN trained using the average ensemble method works best, as shown by results from three different MRI datasets. We utilized three distinct datasets: the binary tumor recognition dataset-I, the Figshare dataset-II, and the multiclass Kaggle dataset-III.They were 98.35%, 98.13%, and 98.67% accurate, respectively. Comparing to current methods, the suggested structure gets better outcomes by combining fine and coarse traits, which makes it useful. [22]

R. C. Christodoulou et.al. (2025) In this study authors showed a Framework for Features Concatenation-based Brain Tumor Classification (FCBTC) that uses Hybrid Deep Learning Models to gather different kinds of data from different feature sets. they started with ResNet50, VGG16, and DensetNet121, which are all models that have already been trained. The blend models they suggested are made up of feature vectors that are fused together. In the end, the testing phase showed that the FCBTC Model-3 had an Accuracy of 98.40%, a Precision of 98.33%, a Recall of 98.26%, and an F1-score of 98.27%. Theory that features variety makes the classifier work better is supported by this. In the end, work's comparative performance evaluation shows that the hybrid FCBTC models authors proposed worked better than other baseline models they suggested. [23]

C. Cueto-Ureña et.al. (2025) This study looked on Radiopharmaceuticals based on Lu-177, PET tracers that target CXCR4, and nanoparticles that can do more than one thing are some of the new theranostic agents. Recently, nanotheranostics had become popular as a way to deliver drugs precisely and monitor them in real time. AI-powered algorithms could make image interpretation and therapy guidance a lot better. However, problems like inconsistent data, regulatory issues, and limited multicenter validation have been pointed out. After careful consideration, the reviewers had decided that combining AI and theranostic technologies could

greatly enhance precise medicine in neuro-oncology. For now, though, it stresses the need for collaborative, cross-disciplinary study to solve the current issues and make the technology widely available in clinical settings.[24]

F. Ghribi et.al. (2025) This paper presented a new hybrid method and offers a new hybrid deep learning framework. This framework takes advantage of both a convolutional neural network's (CNN) and a fine-tuned vision transformer's (ViT) abilities to extract hierarchical features and describe global context. In the tests to see how well the suggested method worked, two well-known MRI datasets were used. The first set of data had 7,023 MRI pictures that were labeled as either having gliomas, meningiomas, pituitary tumors, or no tumors at all. The second set of data came from a search on Kaggle. It had 3,000 scans of brains, with an equal number of healthy brains and brains with cancer. Findings: The suggested architecture gives a strong, comprehensible answer that fits with clinical procedures. A big problem with standard CNNs and pure ViTs is that they don't use data well. This fixes that problem. These findings show how useful mixed approaches can be in the field of neuro-oncology. AI can also be used to make better diagnoses thanks to them. The suggested approach worked very well on these two datasets, getting it right 99.46% of the time and 99.90% of the time. In the end, more research needs to be done on multi-institutional evaluation and computational optimization to make sure the system can be used in a wide range of clinical settings.[25]

M. A. Gómez-Guzmánet.al. (2025) This paper proposed a new type of double ensemble structure. When pre-trained DL models were used for feature extraction, they complement ML classifiers that perform well for stable classification. The procedure kicks off with thorough MRI data addition and preprocessing. It then uses transfer learning with Vision Transformer (ViT) networks that have already been trained to pull out deep features from brain MRIs. One group uses deep features from the best ViT models, and the other is made up of predictions from several machine learning algorithms that have been tweaked for hyperparameters. This two-level group method is what makes our method unique. This plan works better than the best methods used now, as shown by two public Kaggle MRI brain tumor datasets. This is why it's important to use both traits and models together. The suggested way also shows how important it is to use advanced preprocessing and hyperparameter optimization to make medical image analysis more accurate and trustworthy for diagnosis. This is a step toward combining DL and ML in this important and clinically relevant task.[26]

S. C. Gupta et.al. (2025) This study review on brain tumors damaged the brain's structure and function, neuroplastic responses can often keep important functions. they gathered the latest information on the molecular processes that cause neuroplasticity in tumor growth, from the

earliest steps of genetic and protein changes to the most extensive reorganization of function. In this discussion includes how morphological changes, trophic factors, chemicals that are controlled by stress, and synaptic proteins all help adaptive reactions. Connecting small-scale biological processes to large-scale network changes also has clinical implications for glioma surgery and patient results. The knowledge of plasticity's dynamics, predictions, and therapeutic regulation is still lacking, so they need more longitudinal and translational study. Cognitive recovery and quality of life for people with brain tumors could be improved by understanding and using these molecular processes. [27]

A. T. Ibrahimet.al. (2025) This paper presented a look on chemical Hydroxytyrosol (HTX) make-up, how it works, how much you can take, and how well it crosses the blood-brain barrier. Most cancers of the CNS, like gliomas and IDH-wildtype glioblastoma, are very aggressive, don't respond to normal treatment, and have a bad outlook. The basic processes that help them grow include inflammation, autophagy, oxidative stress, and cell death. In animal models of disease, a phenolic substance in olives called Hydroxytyrosol (HTX) has a big effect on these pathways. Making HTX work better in brain cells is possible in many ways. A very small bit can still get there, even though it breaks down very quickly. Many things that happen inside cells are changed by HTX, such as inflammation, planned cell death, and autophagy. Genes can also be produced in different ways through epigenetic processes. Scientists have shown that apoptosis can stop the growth of tumors but not cells that aren't cancers. It's very hard to treat brain tumors like gliomas and IDH-wildtype GBM because they are so aggressive. Most people who get them don't make it. Some of the biological processes that impact their growth are apoptosis, inflammation, oxidative stress, and autophagy. HTP, a chemical found in olives, has been shown by experts to play a key role in these processes. What ingredients are in it, how bioavailable it is, and how well it can cross the blood–brain barrier is also looked at. You can still get small amounts of HTX to the brain, even though its metabolism is very fast. It can also get to nerve cells faster if it is made in different ways. When HTX is present, it controls redox balance, inflammation, planned cell death, and autophagy. Nrf2, NF-κB, JAK/STAT, PI3K/Akt, and SIRT1 are some of the cell processes that it changes to do this. through epigenetic processes, it can also change the way genes are made.According to cell models, it stops tumors from growing and starts the apoptotic process, but it doesn't affect cells that aren't tumors. Furthermore, these findings suggest that it might be useful as an extra aid in the treatment of brain tumors, though more research in animal and human models is needed. [28]

K.-Y. Liu et.al. (2025) This study proposed fully understand how mental dysfunction affects survival, resilience, and quality of life. The brain tumors can cause a lot of neuropsychiatric

problems that often show up before they are found on x-ray. This makes it harder to tell them apart from serious mental diseases. These disorders, which depend on tumors, are caused by changes in metabolism, activity of the immune system, malfunctioning of neurotransmitters, and breaking up of large-scale circuits. One type of dinucleotide hypermethylation is seen in diseases like IDH-mutant gliomas. It leads which can cause hypermethylation of serotonin and glutamatergic pathways and a cognitive-affective condition that doesn't respond to treatment. The damage caused by glutamate excitotoxicity gets worse when high-grade gliomas make too much of the system Xc transporter. This makes your emotions and thoughts change. The blood-brain barrier (BBB) may break down when tumors release cytokines such as IL-6, TNF-α, and IFN-γ, according to some scientists. People with autoimmune encephalopathies and schizophrenia spectrum diseases are more likely to have neuroinflammatory processes get worse. Most people who have frontal gliomas don't care about anything and don't want to do anything.People with temporal tumors, on the other hand, experience hallucinations, mental instability, and failure to remember things sometimes. Cancer-related neuropsychiatric dysfunction is becoming more well known, but it is still underdiagnosed and often wrongly diagnosed. Through the integration of neuroimaging, computational psychiatry, neuroimmunology, and molecular oncology, our initiative aims to enhance our understanding of the underlying mechanisms of these disorders. Potentially useful novel tools for early detection and highly targeted treatments include lesion-network mapping, exosomal biomarkers, and AI-based prediction models. Because conventional psychotropic treatments have their limitations, mechanistically informed therapies such as neuromodulation, neuroimmune-based therapy, and metabolic reprogramming have the potential to enhance psychiatric and oncological outcomes. For paraneoplastic neuropsychiatric illnesses, which are not a result of the tumor itself, but rather parts of its biology, that need to be looked at differently when diagnosing and treating them. The next step in precision psychiatry in neuro-oncology will be to figure out how these problems work at the molecular and circuit levels. [29]

M. Șerban et.al. (2025) This research's main goal was to create and test a care plan for people who have had small brain tumors surgically removed. There are not many programs that help people who have had surgery for a brain tumor get better and meet their social, practical, and informational needs after surgery. Approaches: A quasi-experimental approach was used for the study, and the control group took tests before and after the study, but not at the same time. A program with eight sessions over eight weeks was made using the ADDIE model. It was administered to 65 patients who had been discharged from the hospital, with 32 patients serving as controls and 33 as interventionists. It assessed quality of life using the (FACIT), adjusted

post-discharge symptom severity using the Post-Departure Symptom Assessment Scale (PDCDS), and examined symptom categories using the (MSAS). Both the intervention and control groups interacted significantly during group time for symptom clusters, post-release adaptability, and quality of life in all domains. Changes that were clinically important were seen in every member of the intervention group. The data show that the post-discharge care program helped people with benign brain tumors who had surgery with their symptom clusters, getting used to life after surgery, and quality of life. In clinical practice, the approach can help improve the health of this group of people.[30]

F. A. Tofan et.al. (2025) This study proposed to aims to review the existing literature on GTR and supramarginal resection and compare their respective results. Procedures and Materials: Patients who had either supramarginal or extensive complete excision for brain metastases of any kind were the subjects of a search that included the following databases: End result: The participants' ages ranged from 51 ± 6 to 60.5 ± 10.1 years, on average. Of the overall population, men made up 48.7 percent. Under the random effect model, the frequency of 1-year survival was 91.3% in the supramarginal resection group and 37.1% in the GTR group (0.551, 95% CI [0.18, 0.921]). Under the random effect model, the 2-year survival rate for the GTR group was 21.26%, while for the supramarginal resection group it was 72.46% (0.380, 95% CI [0.113, 0.648]). Under the random effect model, there was a 57.69% local recurrence rate in the GTR group and an 18.4% rate in the supramarginal resection group (0.266, 95% CI [0.106, 0.426]).

Z. Ullah et.al. (2025) This paper presented research on some problems with ViTs that make models less useful. For example, they need very big datasets that have been labeled. With the help of ViT3D, they'd found a new way to divide brain tumors. These issues can be fixed with this method, which blends global context modeling with local feature extraction. When they found a good fusion method that uses upsampling and convolutional tuning, they were able to merge features from different scales better. their method was different from others because it improved the quality of defining the edges of tumors by adjusting local features directly while keeping connections between them globally. They tested their method on the BraTS 2020 dataset. It got a world accuracy score of 99.56%, an average Dice similarity coefficient (DSC) of 77.43% (for all three tumor subregions), and an annual Intersection over Union (IoU) of 71.69%.The individual Dice scores for WT were 84.35%, TC had 80.97%, and ET had 66.97%. The thorough test results showed that our model not only accurately and reliably locates

tumors, but it also does a better job than a number of current top-of-the-line methods, such as U-Net, SwinUnet, M-Unet, and others.[32]

L. Vinueza et al. (2025) This study recommended better treatment options, and detecting brain tumors fast and precisely using MRI scans is critical for helping patients fare better. Tumors appear in a variety of shapes and sizes, there is insufficient labeled medical data, and deep learning models require a significant amount of computing power, making it difficult to develop reliable automated diagnosis tools. The employees stated that the deep learning technique for detecting and classifying brain tumors is reliable and can be utilized by a large number of people. It operates thanks to a two-stage transfer learning mechanism and an improved YOLO-v11 design. In the first stage, a variety of MRI pictures are used to train a simple model. When the mean Average Precision (mAP) approaches 90%, they call it the Brain Tumor Detection Model (BTDM). Step two is to train BTDM on a smaller, separate dataset for use in brain tumor identification and segmentation (BTDS). Despite the fact that the amount of data transferred is limited, domain transfer maintains fast speeds. When domain-specific data is introduced, the model undergoes geometric modifications that increase its generalizability and adaptability. The framework routinely outperforms the best approaches for several types of cancers, including gliomas, meningiomas, and pituitary tumors, as evidenced by tests on publicly available data. For mAP@0.5, the BTDS can reach 91% and the BTDM up to 93.5%. It would be easier to grasp if there was a post-processing module that generated segmentation masks and extracted clinically relevant information such as tumor size and severity level. The results demonstrated that their technology might be employed as a powerful, simple, and effective clinical decision-support tool. This would enable the field of smart real-time neuro-oncological diagnostics expand. [33]

T. Yang, et al. (2025) The study applied a majority vote ensemble method to T1-weighted MRI brain images and assessed multiple CNN models to determine which one did the best job of classifying the data. Approaches: Seven previously trained CNN designs were fine-tuned to distinguish between glioblastoma, meningioma, pituitary adenoma, and no tumor. Each model was trained with two optimizers, SGDM and ADAM, before being tested on a publicly available dataset divided into training (70%), validation (10%), and testing (20%) subsets. To determine whether the models might be utilized in other contexts, they were evaluated again on a separate dataset from the study. After all fourteen models had been trained and their results compiled, an ensemble with majority voting was formed. The ROC curves, confusion matrix, accuracy, precision, and true positive rate were utilized to assess success. On an

individual basis, the best two models for object classification were GoogLeNet and Inception-v3 with ADAM, both with 0.987 scores. The ensemble method outperformed the individual models in terms of accuracy, AUC for all tumor types, and Kappa coefficient. The ensemble improved sensitivity, accuracy, and overall robustness. Findings: When a majority vote ensemble of several CNN architectures was used instead of individual models, MRI-based brain tumor classification performed much better. The results demonstrate the importance of model variety and ensemble learning in developing reliable AI-based neuro-oncology diagnostic tools. [34]

E.M. Younis et al. (2025) This paper introduced a new multi-modal segment anything model (MSAM) capable of segmenting glioma tumors by merging structural MRI and diffusion tensor imaging data. Nous created a viable multimodal feature fusion block that can combine information from multiple data sources to increase brain tumor segmentation accuracy. They developed a training method that effectively addresses the issue of missing modalities in real-world clinical settings. To determine how well it works, experiments were conducted comparing MSAM's success with U-Net across a variety of modality combinations. When only structural mode data is used, MSAM typically outperforms U-Net in terms of 95% Hausdorff Distance and Dice Similarity Coefficients. We demonstrate MSAM's ability to operate with missing data using feature presentation and missing mode training. This implies that strong classification can occur even when crucial senses are not present. The size of the growing area also influences how well it is segmented; smaller portions are more difficult to separate. These findings indicated that MSAM could be effective in clinical scenarios where there is insufficient comprehensive data or tumor sizes are not uniform. [35]

J. Xing et al. (2025) This article discussed how long non-coding RNAs (lncRNAs) are out of sync, and how malignancies frequently exhibit variations in gene expression. Long non-coding RNAs (LncRNAs) have an important role in brain cancer processes such as cell proliferation, cell cycle arrest, and metastasis, whether as tumor drivers or suppressors. Their actions are governed by regulatory processes that occur both before and after transcription. Because lncRNAs are synthesized differently in tumors compared to healthy tissue, it was critical to understand their role in malignant brain tumors. These compounds piqued the interest of cancer researchers because they could serve as biomarkers or therapeutic targets. This paper reviewed what is currently known about lncRNAs and brain cancer. They need to conduct further research to completely grasp their role in drug resistance and how they connect to diverse pathways. If they understood more about lncRNAs and how they affect brain cancer,

we might be able to detect and treat it earlier, increasing the likelihood of a successful outcome. [36]

A lot of progress has been achieved in combining deep learning and hybrid computing to locate brain tumors, classify them into groups, and label them using MRI images, as evidenced in experiments conducted from 2023 to 2025.

N. M. Hassan et al. (2025) This research developed an efficient method for detecting and classifying brain tumors that combines fuzzy thresholding with deep learning techniques. The methodology used fuzzy logic-based preprocessing to improve image quality and minimize noise, followed by a convolutional neural network for feature extraction and classification. The hybrid technique outperformed with 98.7% accuracy, 98.5% sensitivity, and 99.1% specificity. The fuzzy thresholding technique efficiently addressed intensity changes in MRI data, resulting in better tumor boundary detection. Reduced training time improved computational efficiency when compared to standard deep learning approaches. The model performed well across several tumor types, demonstrating clinical usefulness for automated diagnostic systems in radiology departments. [37]

H. Alshaari et al. (2025) This study presents Deep-EFNet, an optimized EfficientNetB0 architecture with dual regularization algorithms for scalable multi-class brain tumor classification. The architecture used both L1 and L2 regularization to prevent overfitting while preserving model complexity. Transfer learning from ImageNet weights was used with fine-tuning on brain tumor MRI datasets. The study divided tumors into four categories: glioma, meningioma, pituitary, and normal tissues. Deep-EFNet obtained 99.1% classification accuracy, 98.8% precision, and 98.9% recall in all classes. [38]

R. Zaitoon et al. (2025) In this publication, researchers developed SPBTGNS, a novel model for predicting survival in brain tumor patients that combines Generative Adversarial Networks (GANs) with Neural Architecture Search (NAS) operations. To overcome dataset imbalance, the GAN framework created synthetic patient data, and NAS automatically adjusted network design for survival prediction tasks. Clinical parameters such as tumor grade, size, location, and patient demographics were combined with imaging data. The model predicted patient survival outcomes with 94.3% accuracy (AUC-ROC = 0.96). [39]

M. Tariq et al. (2025) In this study, researchers improved brain tumor identification by combining Vision Transformers (ViT) and EfficientNetV2 for multi-class classification. The

hybrid design used ViT's self-attention methods to capture global context and long-term dependencies, while EfficientNetV2 retrieved local spatial data effectively. The model processed multi-modal MRI sequences such as T1, T2, and FLAIR images. Classification accuracy reached 98.9%, with particularly strong performance in the glioma (99.2%), meningioma (98.7%), and pituitary tumor (98.8%) classes. The attention mechanism visualization highlighted tumor-specific feature localization, which improved model interpretability. The optimized architecture of EfficientNetV2 kept computational efficiency high, allowing for speedier inference times. The transformer-based technique beat typical CNN designs by 3-5%, indicating the supremacy of attention mechanisms in medical image processing and setting new standards for brain tumor classification. [40]

W. Mehmood et al. (2025) The major difficulty of missing MRI modalities in clinical contexts was solved in this study using a non-negative matrix tri-factorization technique. The methodology split existing imaging data into three factor matrices, allowing for the reconstruction of missing modalities while maintaining anatomical and pathological information. The study focused on real-world clinical scenarios in which complete multi-modal MRI sequences were not possible due to patient contraindications or time restrictions. Despite 50% missing modalities, the imputation strategy obtained 97.5% diagnosis accuracy, indicating its robustness in incomplete data circumstances. [41]

S. Davar et al. (2025) This study improved the U-Net architecture specifically for brain tumor detection and segmentation in T1-weighted MRI data. The updated architecture improved feature propagation and focused on tumor boundaries by using residual connections, dense skip paths, and attention gates. Multi-scale feature fusion across decoder layers gathered both fine-grained features and global context. The improved U-Net achieved 96.8% Dice similarity coefficient, 95.7% sensitivity, and 98.3% specificity for tumor segmentation. Boundary delineation accuracy increased dramatically as compared to standard U-Net, especially for unusual tumor forms. [42]

Y. Ge et al. (2025) In this study researcher developed a novel framework addressing multimodal brain tumor detection with limited labeled data, a common challenge in medical imaging. The approach combined semi-supervised learning with cross-modal knowledge distillation, leveraging unlabeled data effectively. Self-supervised pretraining on unlabeled MRI scans created robust feature representations before fine-tuning on limited annotations. The framework integrated T1, T2, FLAIR, and T1CE modalities through attention-based

fusion mechanisms. With only 20% labeled data, the model achieved 97.2% detection accuracy, approaching fully-supervised performance (98.1%).[43]

Asif et al. in (2025) It was suggested by the author that we use TDAConvAttentionNet, which combines topological data analysis with attention and ConvNeXt modules, to get better Dice scores and lower segmentation mistakes. Overall, these works stress the need to move toward hybrid, attention-driven, and topology-aware architectures to enhance the accuracy, generalizability, and clinical reliability of brain tumor diagnosis.[44]

Q. Yao et al. (2024) This paper improved YOLOv8 architecture for brain tumor detection by integrating attention mechanisms and modified feature pyramids. The enhanced model achieved 96.4% accuracy and 94.7% mAP while maintaining 45 FPS real-time performance. The approach effectively detected small tumors and irregular lesions, demonstrating superior localization compared to traditional methods. Reduced false positives and improved boundary precision validated its clinical applicability for automated radiological screening. [45]

S. M. Malakouti et.al. (2024) The goal of this work was using number data and MRI images to sort healthy and sick people into groups, which uses both machine learning and transfer learning methods. The following techniques were used: Random Forest, Linear Discriminant Analysis, Quadratic Discriminant Analysis, LightGBM, AdaBoost, gradient boosting, 3762 MRI images, and logistic regression. When numerical data was handled with LightGBM, an accuracy of 95.7% was reached. Using a tweaked GoogleNet model for transfer learning on picture data raised the accuracy of classification to 99.3%.[46]

M. Ghorbianet.al. (2024) This article reviewed the findings of a systematic literature review (SLR) of machine learning (ML) methods for finding and classifying brain cancers. To find both common and uncommon methods, we looked to the World Health Organization's classical classification. We also presented open subjects and essential issues. Based on the World Health Organization's classifications, taxonomy is offered in four primary areas: Levels 1, 2, 3, and 4. This article talked about machine learning methods for finding and grouping brain tumors based on important factors like evaluation standards, techniques, and pros and cons. Machine Learning (ML), a type of AI, has become more famous for processing and analyzing data. Recently, ML has been used a lot in medicine to find and diagnose illnesses in their early stages, like brain tumors. This new technology makes it easier to find and treat brain tumors more quickly and more accurately. However, it is important to note that ML results still need to be checked and approved by medical workers and experts in the field. The importance of correctly identifying types of tumors and planning treatment plans, along with the variety of methods used in machine learning, necessitates a thorough investigation into the dependability

and precision of these methods. Some of the trickiest parts of employing ML technology are making an early diagnosis and getting the classifications right. Even though problems with diagnosis and treatment are very important in healthcare, as far currently know, no complete study of machine learning techniques for classifying and diagnosing brain tumors according to WHO standards has been done. [47]

E.Y. Shchetinin et.al. (2024) This study proposed a U-Net architecture-based deep neural network model, these U-Net encoders are deep convolutional neural network models that have already been trained on the ImageNet dataset. Multiple models were used, such as Inception, Efficientnetb7, InceptionResnetV2, DenseNet201, DenseNet121, Mobilenetv2, VGG19, and VGG19. Based on an experiment involving MRI brain scans and computer science, the DenseNet121 model was determined to be the optimal encoder model for the deep models mentioned before, when combined with the segmentation metrics provided below. In a 94.22% accuracy rate, the dice land on the correct side of the table 94.13% of the time. On top of that, the findings of the proposed segmentation approach are compared to those of other papers in the publication. Examining the segmentation outcomes of the analyzed MRI images revealed that the DenseNet121 model outperformed or was equally accurate as the models proposed in the scholarly articles regarding segmentation precision.[48]

M. Aamir et.al. (2024) The proposed study presents a model of a hyperparametric CNN for the detection of brain cancers. Improved accuracy in diagnosing brain tumors is achieved by optimizing feature extraction and methodically reducing model complexity through CNN hyperparameter adjustment. Size of the batch, number of layers, activation functions, learning rate, pooling techniques, padding, and filter size are all crucial hyperparameters. Accuracy, precision, recall, and F1-score all averaged out to 97% after training the hyperparameter-tuned CNN model on three separate brain MRI datasets made available on Kaggle. By systematically comparing our optimized model against state-of-the-art methods, we have proven its effectiveness. By changing the model's hyperparameters, we made it work better and be more useful in other situations. This gives doctors a better tool for making important decisions about finding brain tumors. The approach we use isn't without its flaws, but it's a giant leap forward for accurate medical diagnosis that can benefit patients. in the text.

A. Singh et.al. (2024) In this Study a hyperparametric CNN model for tumor detection in the brain was developed by researchers. This materializes in the actual world and yields substantial results. A more precise diagnosis of brain tumors is achieved by fine-tuning CNN hyperparameters and optimizing feature extraction, both of which significantly reduce model complexity. The learning rate, activation functions, batch size, layer numbers, pooling

methods, padding, and filter size are critical hyperparameters. The average F1-score, recall, accuracy, and precision after training the hyperparameter-tuned convolutional neural network (CNN) model on three separate brain MRI datasets made public on Kaggle were all 97%. We demonstrated the efficacy of our optimized model by methodically comparing it against state-of-the-art approaches. By adjusting the model's hyperparameters, we improved its performance and generalizability, providing doctors with a better tool for making important decisions about brain tumor detection. The author model is a significant step in the right direction toward trust. [50]

T. Rahman, et.al. (2024) This research suggested a new way to classify things that uses progressive image resizing and a hybrid attention mechanism to work better A mix of preprocessing techniques, reconstructing transfer learning architectures, and dynamic fine-tuning strategies make up the approach. Critical hyper-parameters were optimized in this study using the Dynamic Chaotic Whale Optimization Algorithm. To make training even more effective and the model more flexible, we also made a new learning rate scheduler that changes the learning rate during each training phase based on the size of the picture. The picture size changed how the layers were frozen and how big each batch was. Their ensemble method used weighted averaging, bagging, boosting, stacking, mixing, and voting to combine the results of models that were trained on different picture sizes. They tested our suggested method with benchmark datasets and got amazing results: it was 99.67%, 99.09%, and 99.67% accurate compared to the usual methods.[51]

N. F. Alhussainan, et.al. (2024) This Study proposed the Res-BRNet is a new structure for deep residual and region-based CNNs that can sort brain tumors from MRI images. It can get around this problem. With the help of boundaries and regions, Res-BRNet plans how to join processes in changed spatial and residual blocks. The blocks in space get the traits of brain tumors that have to do with uniformity, heterogeneity, and boundaries. The leftover blocks get the changes in texture that happen locally and globally. It tested Res-BRNet on some tough images from the Br35H, figshare, and Kaggle libraries. These pictures included meningiomas, gliomas, pituitary tumors, and healthy people. However, Res-BRNet, which had an F1-score of 0.9841, sensitivity of 0.9812, precision of 0.9822, and accuracy of 98.22%, was better than the other CNN models. From what we saw, Res-BRNet looks like a good way to divide brain tumors into various types. This could help doctors figure out what's wrong faster and more accurately.[52]

A. Abdullah et al. (2024) This article presented a two-module computerized way to find brain tumors. Image Enhancement Techniques like adaptive Wiener filtering, neural networks, and

independent component analysis are used in the first part to make MRI images look better and more normal. Support Vector Machines are used to divide and classify tumors in the second section. .[53]

A. Younis et al. (2024) This study suggested an improved deep learning model using ResNet50 to sort brain tumors into three groups: meningiomas, gliomas, and pituitary tumors. The model was correct 99% of the time on both the training and test datasets. It was also correct 98% of the time in its own class and had a precision of 0.983. Used extra data and transfer learning to make generalization better.[54]

S. M. Alqhtaniet al. (2024) This Study used CLAHE to improve the contrast, Fuzzy C-Means for segmentation, and SVM for classification to create an automatic method for MRI brain tumor segmentation and classification. Got a Dice Score of 0.961, a sensitivity score of 0.977, a precision score of 0.979, and an accuracy score of 0.982. The whole process took 0.42 seconds.[55]

N. Bibi et al. (2024) This Paper Proposed an InceptionV4 model for classifying brain tumors that is based on Transfer Learning. Used files with 7022 images, such as SARTAJ and Br35H. Achieved a 98.7% success rate, tackling difficulties in brain tumor detection with great accuracy and less computer work.[56]

S.G. K. Patro et al. (2024) This article put forwarded a deep learning-based ensemble system for classifying brain tumors from MRI images that worked 99.43% of the time.Before processing an image, it is improved, and seven deep learning models are trained to spot features of a tumor. Focus areas for the future include growing datasets, adding more designs, and improving real-time detection.[57]

P. Chauhan et al. (2024) This study created PBVit, a patch-based Vision Transformer model that accurately caught spatial relationships in MRI scans, showing the power of transformer-based models with a 95.8% success rate.[58]

M. Celik et.al. (2023) In this study, researchers continued to do various investigations in this area due to the low accuracy of multiple classification of these photos. It was thought that both DL models and standard ML algorithms can fulfill the demand to create models that achieve high accuracy on original photos. The hyperparameters must be chosen properly when ML algorithms and DL models are combined. This research suggested a new hybrid approach that can properly group brain tumors in a number of different ways. The success of CNN is also compared using nine top models. It uses the Bayesian optimization method to find the best values for the hyperparameters of machine learning algorithms. According to the experiments,

the suggested hybrid model had an average classification accuracy of 97.15 percent and memory, precision, and F1-score values of 97 percent. [59]

S. Krishnapriya et.al. (2023) This survey presented the current state of MRI-based brain tumor detection utilizing various cutting-edge ML and DL methods. This study focused on the methods, datasets, deep learning architectures, and publicly available images of brain tumors that have been utilized by different researchers for the purpose of detecting these tumors. The paper also talks about the problems, possible solutions, and the current success of deep learning algorithms. It has been checked to see how accurate the different ways that have been suggested so far are. Several studies have found that SVM can improve the accuracy of segmenting and studying MR images to find brain tumors by over 98%. Brain cancer could be found with 99% accuracy by the ANN, which was the best deep learning system for the job. The main point of this study is to show experts new changes in the field that make this hard topic interesting. Digital image processing techniques like filtering, segmentation, and classification can be used to help create computer-aided design (CAD) systems that use MR images to find brain tumors. The main ML and DL ways to find brain tumors are talked about in this article. The images in this study were sorted using a variety of deep learning and machine learning techniques. This study gives an overview of some widely used MR image collections. This study looks at how different types of Magnetic Resonance imaging can be used to make better plans for identifying other brain diseases, such as Parkinson's disease, Alzheimer's disease, dementia, and strokes. [60]

S. Solanki et.al. (2023) This study showed a lot of different ways to find brain tumors and cancer. In addition, this study shows an evaluation matrix for a single system that uses a single set of information and systems. This work talks about the shape of brain tumors, the data sets that are available, methods for adding to them, part extraction, and how DL, TL, and ML models can be used to classify them. Finally, our study gathers all the important information for finding out about tumors, such as their pros and cons, recent progress, and future trends.[61]

K. Neamah et al. (2023) In this article researchers did an in-depth analysis of how deep learning can be used to find brain tumors (2019–2022). In a table comparison, the pros and cons of current methods were emphasized. Given ideas on how to make future deep learning models for finding brain tumors better.[62]

N. Noreen et al. (2023) This paper proposed a multi-level feature extraction with models that have already been trained (Inception-v3 and DenseNet201) is suggested. Softmax was used to combine features and classify them, and it achieved 99.34% and 99.51% accuracy in classifying brain tumors, which was better than other methods that were already available.[63]

Z. Atha et al. (2023) This Paper suggested SSBTCNet, a deep learning method that can help find brain tumors by using Auto Encoders and Multi-Layer Perceptron. Adding things based on fuzzy reasoning to make the system more stable. On different sets of data, the method did better than other ways of identifying brain tumors.[64]

J. Chaki et al. (2023) This study **c**reated a fuzzy logic-based reinforcement learning method (DBIRA2.0-RLN) for brain tumor classification and recall that uses Inception blocks and skip-connections. Multilinear Principal Component Analysis was used to improve the speed of categorization and retrieval by optimizing descriptor vectors.[65]

A. Farzamnia et al. (2023): This study created a method that uses the contourlet transform and whale optimization algorithm to accurately tell the difference between benign and malignant brain tumors from MRI pictures. This method achieved over 98.5% accuracy. Describes new classification methods and how to make runtimes more efficient.[66]

S. M. A. H. Shahet al. (2023): In this study researchers proposed a method VS-BEAM (Voting-Based Semi-Supervised Bayesian Ensemble Attention Mechanism) for automatically separating and classifying MRI tumors. Diagnostic accuracy of 98.91% was reached, which makes it better for practical use.[67]

J. Zhao et al. (2023) This paper proposed approach using a mix of 2D, 2.5D, and 3D CNNs, created an Uncertainty-aware Multi-dimensional Mutual Learning Framework that improved generalization and achieved up to a 2.8% Dice improvement across different datasets.[68]

3.RESEARCH GAP

Despite significant advancements in applying deep learning and machine learning techniques for brain tumor diagnosis using MRI data, several research gaps are-

- Limited image quality and inconsistency across MRI scans
- Redundant and non-optimized feature extraction in CNN models
- Lack of integration of multiple deep learning models for robustness
- Limited clinical readiness and deployment feasibility

Addressing these gaps through improved feature extraction, multi-modal integration, and robust deep learning techniques can significantly enhance their clinical impact.

4. RESEARCH OBJECTIVES

The aim of brain tumor detection is to develop an accurate and reliable system for identifying and classifying brain tumors from medical images. The objectives of brain tumor detection can include:

1. To analysis brain tumor images using preprocessing techniques.
2. To design multi model fusion techniques for tumor detection.
3. Compare the performance of proposed hybrid model against existing model.

5. RESEARCH METHODOLOGY

The proposed methodology for Brain Tumor Detection will involve a systematic deep learning-based image analysis pipeline designed to accurately identify and localize tumor regions from medical imaging datasets. primarily, the input dataset brain MRI images collected with formats such as .png and .jpg, brain MRI images publicly available medical image repository.

First phase is pre-processing in this process, acquired MRI and undergoes with resizing and cropping and filtering enhancement operations, perform to maintain uniform dimensions, grayscale conversion to simplify pixel intensity representation, and segmentation to isolate the region of interest (ROI) corresponding to potential tumor areas. from the segmented images using techniques such as the Gray Level Co-occurrence Matrix (GLCM), and statistical measures including mean, median, and variance, which will capture both spatial relationships and intensity variations within the brain tissues. After that processed images will then be subjected to image splitting, where the dataset will be divided into training and testing subsets—training images will be used to train and optimize the model, while testing images will evaluate the model's prediction.

advanced deep learning architectures will be implemented In the classification phase, such as VGG19, InceptionV3, MobileNet, GoogleNet, and ResNet-50 to classify MRI scans as tumor or non-tumor. Both baseline training and transfer learning strategies will be applied to enhance accuracy and efficiency, with optimization algorithms such as SGDM, RMSProp utilized for adaptive learning and faster convergence. Finally, in the output stage, the trained model will predict whether a given brain MRI image contains a tumor or not, and if detected, the corresponding tumor region will be localized and highlighted on the image for clinical interpretation, thereby assisting radiologists and healthcare professionals in achieving accurate and efficient diagnosis.

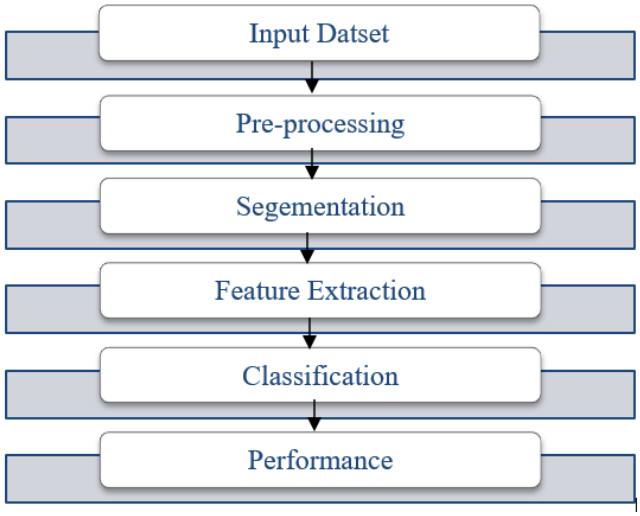

Figure 5.1Standard Flow Diagram

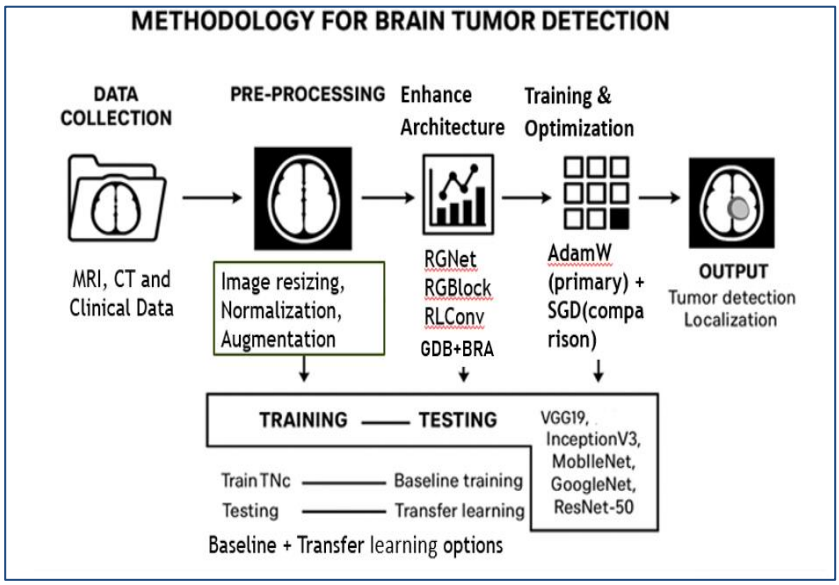

Figure 5.2ProposedFlowDiagram

The methodology diagram illustrates a complete end-to-end workflow for brain tumor detection using medical imaging and deep learning techniques. The process begins with data collection, where MRI scans, CT images, and clinical records are gathered to form a diverse and representative dataset. This raw medical data is then passed into the pre-processing stage, where crucial operations such as image resizing, normalization, and data augmentation are performed to enhance image quality, ensure uniform dimensions, and artificially expand the dataset. These steps help improve model robustness and reduce overfitting.

Following pre-processing, the images enter the enhanced architecture module, where advanced deep learning components—such as RGNet, RGBlock, RLConv, and GDB+BRA—are integrated to strengthen feature extraction, deepen the network's representational power,

and improve sensitivity to tumor patterns. The next stage involves training and optimization, where the model is trained using the AdamW optimizer as the primary choice, with SGD employed for performance comparison. These optimizers adjust network weights efficiently, aiding in faster convergence and improved accuracy.

The workflow then proceeds to training and testing, which incorporate both baseline training and transfer learning approaches. Well-known pre-trained architectures like VGG19, InceptionV3, MobileNet, GoogleNet, and ResNet-50 are used for benchmarking and performance comparison. Transfer learning helps leverage pre-learned visual features, significantly boosting performance on medical imaging tasks. Finally, the system generates the output, which includes tumor detection and localization, highlighting the presence and position of abnormal regions within brain scans. This systematic methodology ensures high accuracy, reproducibility, and clinical relevance in brain tumor detection.

Datasets: There are various datasets are identical so we will work upon any three of them.

1. This dataset contains **7023** images of human brain MRI images which areclassifiedintofourclasses: **glioma** - **meningioma** - **no tumor** and **pituitary**. https://www.kaggle.com/datasets/masoudnickparvar/brain-tumor-mri-dataset
2. This brain tumor dataset containing 3064 T1-weighted contrast-inhanced images from 233 patients with three kinds of brain tumor: meningioma (708 slices), glioma (1426 slices),andpituitary tumor (930 slices).https://www.kaggle.com/datasets/denizkavi1/brain-tumor
3. The folder contains MRI data. The images are already split into Training and Testing folders. Each folder has more four subfolders. These folders have MRIs of respective tumorclasses. https://www.kaggle.com/datasets/sartajbhuvaji/brain-tumor-classification-mri/dat

6. WORKPLAN OF RESEARCH

RESEARCH ACTIVITY	Months						
	6	12	18	24	30	36	*
1. Course work							
2. Literature survey			Review paper				
3. Methodology steps				Objective 1 Paper			
4. Quarterly reports							
5. Communication of papers					Objective 2 and 3 Paper		
6. Preparation of final thesis							
7. Submission of thesis							

To achieve three objectives of my research we divided research into three phases:

PHASE 1: To achieve objective 1

- Collection of datasets from Kaggle
- Preprocessing of data: Grayscale conversion, Normalisation, Data Augmentation,
- Write and publish a comprehensive review paper in repudiated conference

PHASE 2: To achieve Objective 2

- Implementation of Objective 1 data preprocessing and base model development
- preliminary experiments
- Published research paper in conference and Journal.

PHASE 3: Objective: To Achieve Objective 3

- Complete model training for Objectives 2 and 3
- conduct extensive experiments and analyse results
- publish research papers in Journal and prepare final thesis
- This phase includes comprehensive evaluation, comparative analysis, and documentation of findings

7. REFERENCES

1. H. Mehnatkash, S. M. Jalali, A. Khosravi,S.Nahavandi .“An intelligent driven deep residual learning framework for brain tumour classification using MRI images. Expert Syst Appl 2023 Mar 1;213:119087.
2. M. A. Haq, I. Khan, A. Ahmed, S. M. Eldin, A. Alshehri, and N. A. Ghamry, "DCNNBT: a novel deep convolution neural network-based brain tumor classification model. Fractals 2023 May 20:2340102.
3. A. A. Asiri, A. Shaf, T. Ali, M. Aamir, A. Usman, M. Irfan, H. A. Alshamrani, KM Mehdar, OM Alshehri, SM Alqhtani. “Multi-level deep generative adversarial networks for brain tumor classification on magnetic resonance images.” Intelligent Automation & Soft Computing 2023 Apr 1;(1):36.
4. S.A. Qureshi, S.E.A. Raza, L. Hussain, A. A. Malibari, M. K. Nour, A. U. Rehman, Al-Wesabi, F.N.; Hilal, A.M. “Intelligent Ultra-Light Deep Learning Model for Multi-Class Brain Tumor Detection.” *Appl. Sci.* **2022**, *12*, 3715.
5. M.M. Zahoor,S. A. Qureshi, S. Bibi, S.H. Khan, A. Khan, U. Ghafoor, M.R. Bhutta, M.R. “A New Deep Hybrid Boosted and Ensemble Learning-Based Brain Tumor Analysis Using MRI.” *Sensors* **2022**, *22*, 2726.
6. M. Arabahmadi,R. Farahbakhsh, J. Rezazadeh, “Deep Learning for Smart Healthcare—A Survey on Brain Tumor Detection from Medical Imaging.” *Sensors* **2022**, *22*, 1960.
7. D.V. Gore, V. Deshpande. ” Comparative study of various techniques using deep Learning for brain tumor detection.” In Proceedings of the 2020 IEEE International Conference for Emerging Technology (INCET), Belgaum, India, 5–7 June 2020; pp. 1–4.
8. L. M. DeAngelis,Brain tumors. *N. Engl. J. Med.* **2001**, *344*, 114–123.
9. V. Y. Borole, S. S. Nimbhore, D. S. S. Kawthekar. “Image processing techniques for brain tumor detection:” A review. *Int. J. Emerg. Trends Technol. Comput. Sci. (IJETTCS)* **2015**, *4*, 2.
10. J. Amin,M. Sharif,M. Yasmin,S. L. Fernandes,“Big data analysis for brain tumor detection: Deep convolutional neural networks.” *Future Gener. Comput. Syst.* **2018**, *87*, 290–297.
11. Iorgulescu, J.B.; Sun, C.; Neff, C.; Cioffi, G.; Gutierrez, C.; Kruchko, C.; Ruhl, J.; Waite, K.A.; Negoita, S.; Hofferkamp, J.; et al. Molecular biomarker-defined brain tumors: Epidemiology, validity, and completeness in the United States. *Neuro-Oncology* **2022**, *24*, 1989–2000.

12. S. Cha, “Update on brain tumor imaging: From anatomy to physiology”. *Am. J. Neuroradiol.* **2006**, *27*, 475–487.
13. Ranjbarzadeh, R.; Bagherian Kasgari, A.; Jafarzadeh Ghoushchi, S.; Anari, S.; Naseri, M.; Bendechache, M. Brain tumor segmentation based on deep learning and an attention mechanism using MRI multi-modalities brain images. *Sci. Rep.* **2021**, *11*, 10930.
14. Rahman, M.L.; Reza, A.W.; Shabuj, S.I. An internet of things-based automatic brain tumor detection system. *Indones. J. Electr. Eng. Comput. Sci.* **2022**, *25*, 214–222.
15. Key Statistics for Brain and Spinal Cord Tumors. Available online: https://www.cancer.org/cancer/brain-spinal-cord-tumorsadults/about/key-statistics.html (accessed on 12 February 2023).
16. W. Ayadi,Elhamzi, W.; Charfi, I.; Atri, M. Deep CNN for Brain Tumor Classification. *Neural Process. Lett.* **2021**, *53*, 671–700.]
17. A. l. -Galal, S.A.Y.; Alshaikhli, I.F.T.; Abdulrazzaq, M.M. MRI brain tumor medical images analysis using deep learning techniques: A systematic review. *Health Technol.* **2021**, *11*, 267–282.
18. Mahmud, M.I.; Mamun, M.; Abdelgawad, A. A Deep Analysis of Brain Tumor Detection from MRIImages Using Deep Learning Networks. *Algorithms* **2023**, *16*, 176.
19. ZainEldin, H.; Gamel, S.A.; El-Kenawy, E.-S.M.; Alharbi, A.H.; Khafaga, D.S.; Ibrahim, A.; Talaat, F.M. Brain Tumor Detection and Classification Using Deep Learning and Sine-Cosine Fitness GreyWolf Optimization. *Bioengineering* **2023**, *10*, 18.
20. P.G. Rajan, and C. Sundar, “Brain Tumor Detection and Segmentation by Intensity Adjustment,” in Journal of Medical Systems, ACM, 2019.
21. Kora P, Mohammed S, Teja MJ, Kumari CU, Swaraja K, Meenakshi K. “Brain tumor detection with transfer learning”. In2021 fifth international conference on I-smac (IoT in social, mobile, analytics and cloud)(I- SMAC) 2021 nov 11 (pp. 443-446). IEEE.
22. S. Aksoy, P. Demircioglu, I. Bogrekci, I. (2025). A web-deployed, explainable AI system for comprehensive brain tumor diagnosis. Neurological International, 17(8), 121. https://doi.org/10.3390/neurolint17080121
23. R. Christodoulou, P. S. Papageorgiou, R. Pitsillos, A. Woodward, S. G. Papageorgiou, E. E. E. E., &M. F. Georgiou, M. F. (2025). A narrative review of theranostics in neuro-oncology: Advancing brain tumor diagnosis and treatment through nuclear medicine and artificial intelligence. International Journal of Molecular Sciences, 26(15), 7396. https://doi.org/10.3390/ijms26157396

24. Cueto-Ureña, C., Ramírez-Expósito, M. J., Carrera-González, M. P., & Martínez-Martos, J. M. (2025). Hydroxytyrosol and brain tumors: Mechanisms of action and therapeutic potential. Current Issues in Molecular Biology, 47(8), 667. https://doi.org/10.3390/cimb47080667
25. F. Ghribi, F. Hamdaoui, (2025). A novel 3D U-Net–Vision Transformer hybrid with multi-scale fusion for precision multimodal brain tumor segmentation in 3D MRI. Electronics, 14(18), 3604. https://doi.org/10.3390/electronics14183604
26. M.A. Gómez-Guzmán, L. Jiménez-Beristain, E. E. García-Guerrero, O.A. Aguirre-Castro,J. J. Esqueda-Elizondo, E. R. Ramos-Acosta, Galindo-Aldana, G. M., Torres-Gonzalez, C., & Inzunza-Gonzalez, E. (2025). Enhanced multi-class brain tumor classification in MRI using pre-trained CNNs and transformer architectures. Technologies, 13(9), 379. https://doi.org/10.3390/technologies13090379
27. S. C. Gupta, S. Vijayvargiya, V. Bhattacharjee,(2025). Role of feature diversity in the performance of hybrid models—An investigation of brain tumor classification from brain MRI scans. Diagnostics, 15(15), 1863. https://doi.org/10.3390/diagnostics15151863
28. A. T. Ibrahim, I. H. Abdullahi, M.Donfack Kana, A. F., Abubakar, A. H., Mohammed, M. T., Gabralla, L. A., Rusydi, M. K., &Chiroma, H. (2025). Hybrid attention-enhanced Xception and dynamic chaotic whale optimization for brain tumor diagnosis. Bioengineering, 12(7), 747. https://doi.org/10.3390/bioengineering12070747
29. K.-Y. Liu, N.-H. Lu, Y.-H.Huang, Matsushima, A., Kimura, K., Okamoto, T., & Chen, T.-B. (2025). Majority voting ensemble of deep CNNs for robust MRI-based brain tumor classification. Diagnostics, 15(14), 1782. https://doi.org/10.3390/diagnostics15141782
30. M. Șerban, C.Toader, & Covache-Busuioc, R.-A. (2025). Brain tumors, AI and psychiatry: Predicting tumor-associated psychiatric syndromes with machine learning and biomarkers. International Journal of Molecular Sciences, 26(17), 8114. https://doi.org/10.3390/ijms26178114
31. F. A. Tofan, Massoud, A. T., Faur, C. I., & Florian, S. I. (2025). Supramarginal resection of metastatic brain tumors: A meta-analysis study. Medicina, 61(8), 1446. https://doi.org/10.3390/medicina61081446
32. Z. Ullah, Kim, J. (2025). Hierarchical deep feature fusion and ensemble learning for enhanced brain tumor MRI classification. Mathematics, 13(17), 2787. https://doi.org/10.3390/math13172787

33. L. Vinueza, Pineda, S., & Leon-Rojas, J. E. (2025). Molecular foundations of neuroplasticity in brain tumors: From microscopic adaptation to functional reorganisation. International Journal of Molecular Sciences, 26(15), 7049. https://doi.org/10.3390/ijms26157049
34. T. Yang, Shin, S., Ahn, Y., & Sok, S. (2025). Effects of a post-discharge care program for surgery patients with brain tumor. Healthcare, 13(17), 2179. https://doi.org/10.3390/healthcare13172179
35. Younis, E. M., Ibrahim, I. A., Mahmoud, M. N., & Albarrak, A. M. (2025). Hybrid of VGG-16 and FTVT-b16 models to enhance brain tumors classification using MRI images. Diagnostics, 15(16), 2014. https://doi.org/10.3390/diagnostics15162014
36. J. Xing,Zhang, J. (2025). Segmentation of brain tumors using a multi-modal segment anything model (MSAM) with missing modality adaptation. Bioengineering, 12(8), 871. https://doi.org/10.3390/bioengineering12080871
37. N. M. H. Hassan and W. Boulila, "Efficient Approach for Brain Tumor Detection and Classification Using Fuzzy Thresholding and Deep Learning Algorithms," IEEE Access, vol. 13, pp. 78808–78832, May 2025, doi: 10.1109/ACCESS.2025.3566332.
38. H. Alshaari and S. Alqahtani, "Deep-EFNet: An Optimized EfficientNetB0 Architecture With Dual Regularization for Scalable Multi-Class Brain Tumor Classification in MRI," IEEE Access, vol. 13, pp. 85682–85697, May 2025, doi: 10.1109/ACCESS.2025.3567919.
39. R. Zaitoon, S. N. Mohanty, D. Godavarthi, and J. V. N. Ramesh, "SPBTGNS: Design of an Efficient Model for Survival Prediction in Brain Tumour Patients Using Generative Adversarial Network With Neural Architectural Search Operations," IEEE Access, vol. 12, pp. 140847–140869, Jul. 2024.
40. M. Tariq, M. Iqbal, M. J. Iqbal, and I. Ahmad, "Transforming Brain Tumor Detection Empowering Multi-Class Classification With Vision Transformers and EfficientNetV2," IEEE Access, vol. 13, pp. 63857–63876, Mar. 2025, doi: 10.1109/ACCESS.2025.3555638.
41. W. Mehmood, A. Sajjad, M. Akmal, and F. Kainat, "Robust Brain Tumor Diagnosis in Clinical MRI Scenarios: A Non-Negative Matrix Tri-Factorization Approach for Missing Modality Imputation," IEEE Access, vol. 13, pp. 154008–154020, Aug. 2025.
42. S. Davar and T. Fevens, "Enhanced U-Net Architecture for Brain Tumor Localization and Segmentation in T1-Weighted MRI," IEEE Trans. Circuits Syst. II: Express Briefs, vol. 72, no. 8, pp. 993–997, Aug. 2025, doi: 10.1109/TCSII.2025.3556846.
43. Y. Ge, L. Xu, X. Wang, Y. Que, and M. J. Piran, "A Novel Framework for Multimodal Brain Tumor Detection With Scarce Labels," IEEE J. Biomed. Health Inform., vol. 29, no. 8, pp. 5368–5380, Aug. 2025, doi: 10.1109/JBHI.2024.3467343.

44. S. Asif, A. R. Shahid, K. Aftab, and S. A. Enam, "Integrating the Prior Shape Knowledge Into Deep Model and Feature Fusion for Topologically Effective Brain Tumor Segmentation," IEEE Access, vol. 13, pp. 99641–99658, Jun. 2025, doi: 10.1109/ACCESS.2025.3577393.
45. Q. Yao, D. Zhuang, Y. Feng, Y. Wang, and J. Liu, "Accurate Detection of Brain Tumor Lesions From Medical Images Based on Improved YOLOv8 Algorithm," IEEE Access, vol. 12, pp. 144260–144279, Oct. 2024, doi: 10.1109/ACCESS.2024.3472039.
46. S. M. Malakouti, Mohammad Bagher Menhaj, Amir Abolfazl Suratgar(2024) "Machine learning and transfer learning techniques for accurate brain tumor classification" Volume 7, December 2024, Pages 106-119, https://doi.org/10.1016/j.ceh.2024.08.001
47. M. Ghorbian , S. Ghorbian , Mostafa Ghobaei-arani (2024)"A comprehensive review on machine learning in brain tumor classification: taxonomy, challenges, and future trends "https://doi.org/10.1016/j.bspc.2024.106774,
48. E.Y. Shchetinin (2024) "Brain tumor segmentation by deep learning transfer methods using MRI images" DOI: 10.18287/2412-6179-CO-1366,
49. Muhammad Aamir , Abdallah Namoun , Sehrish Munir , Nasser Aljohani , Meshari HuwaytimAlanazi , Yaser Alsahafi ,FarisAlotibi (2024) "Brain Tumor Detection and Classification Using an Optimized Convolutional Neural Network " 2024, 14, 1714. https://doi.org/10.3390/ diagnostics14161714, 7 August 2024
50. Aakash singh ,deepawalisharma ,vivekkumarsingh (2024) "mimic: Misogyny Identification in Multimodal Internet Content in Hindi-English Code Mixed Language" http://dx.doi.org/10.1145/3656169
51. Rahman, T., Islam, M. S., & Uddin, J. (2024). MRI-based brain tumor classification using a dilated parallel deep convolutional neural network. Digital, 4(3), 529–554. https://doi.org/10.3390/digital4030027
52. Alhussainan, N. F., Ben Youssef, B., & Ben Ismail, M. M. (2024). A deep learning approach for brain tumor firmness detection based on five different YOLO versions: YOLOv3–YOLOv7. Computation, 12(3), 44. https://doi.org/10.3390/computation12030044
53. Abdullah A. Asiri Toufique Ahmed Soomro; Ahmed Ali Shah; Ganna Pogrebna; Muhammad Irfan; Saeed Alqahtani"Optimized Brain Tumor Detection: A Dual-Module Approach for MRI Image Enhancement and Tumor Classification" DOI: 10.1109/ACCESS.2024.3379136, Page(s): 42868 – 42887, 20 March 2024
54. Ayesha Younis; Qiang Li; Zargaam Afzal; Mohammed Jajere Adamu; Halima Bello Kawuwa; Fida Hussain "Abnormal Brain Tumors Classification Using ResNet50 and Its

Comprehensive Evaluation" DOI: 10.1109/ACCESS.2024.3403902, Page(s): 78843 – 78853, 21 May 2024

55. S. M. Alqhtani; Toufique Ahmed Soomro; Ahmed Ali Shah; Abdul Aziz Memon; Muhammad Irfan; Saifur Rahman(2024) "Improved Brain Tumor Segmentation and Classification in Brain MRI With FCM-SVM: A Diagnostic Approach" DOI: 10.1109/ACCESS.2024.3394541, Page(s): 61312 – 61335, 29 April 2024
56. Nadia Bibi; Fazli Wahid; Yingliang Ma; Sikandar Ali; Irshad Ahmed Abbasi; Ahmed Alkhayyat (2024)"A Transfer Learning-Based Approach for Brain Tumor Classification" DOI: 10.1109/ACCESS.2024.3425469, Page(s): 111218 – 111238, 09 July 2024
57. S Gopal Krishna Patro; Nikhil Govil; Surabhi Saxena; Brojo Kishore Mishra; Abu Taha Zamani; Achraf Ben Miled (2024)"Brain Tumor Classification Using an Ensemble of Deep Learning Techniques" DOI: 10.1109/ACCESS.2024.3485895, Page(s): 162094 – 162106, 24 October 2024
58. P. Chauhan, M. Lunagaria, D. K. Verma, K. Vaghela, G. G. Tejani, and S. K. Sharma, "PBVit: A Patch-Based Vision Transformer for Enhanced Brain Tumor Detection," IEEE Access, vol. 13, pp. 13015–13029, Dec. 2024, doi: 10.1109/ACCESS.2024.3521002.
59. Muhammed Celik , Ozkan Inik(2023) "Development of hybrid models based on deep learning and optimized machine learning algorithms for brain tumor Multi-Classification" https://doi.org/10.1016/j.eswa.2023.122159, 12 October 2023
60. Srigiri Krishnapriy, Yepuganti Karuna(2023) "A survey of deep learning for MRI brain tumor segmentation methods: Trends, challenges, and future directions" https://doi.org/10.1007/s12553-023-00737-3, 7 February 2023
61. Shubhangi Solanki , Uday Pratap Singh , Siddharth Singh Chouhan , And Sanjeev Jain , (2023)"Brain Tumor Detection and Classification Using Intelligence Techniques: An Overview" 10 February 2023.
62. Karrar Neamah; Farhan Mohamed; MyasarMundher Adnan; Tanzila Saba; Saeed Ali Bahaj; Karrar Abdulameer Kadhim (2023)"Brain Tumor Classification and Detection Based DL Models: A Systematic Review" DOI: 10.1109/ACCESS.2023.3347545 Page(s): 2517 – 2542,26 December 2023
63. Neelum Noreen; Sellappan Palaniappan; Abdul Qayyum; Iftikhar Ahmad; Muhammad Imran(2023) Muhammad Shoaib "A Deep Learning Model Based on Concatenation Approach for the Diagnosis of Brain Tumor" DOI: 10.1109/ACCESS.2020.2978629, Page(s): 55135 – 55144, 05 March 2023

64. Z. Atha; Jyotismita Chaki (2023)“SSBTCNet: Semi-Supervised Brain Tumor Classification Network” DOI: 10.1109/ACCESS.2023.3343126, Page(s): 141485 – 141499, 14 December 2023
65. Jyotismita Chaki; Marcin Woźniak (2023)“Brain Tumor Categorization and Retrieval Using Deep Brain Incep Res Architecture Based Reinforcement Learning Network” DOI: 10.1109/ACCESS.2023.3334434, Page(s): 130584 – 130600, 20 November 2023
66. Ali Farzamnia; Seyed Hamidreza Hazaveh; Seyede Safieh Siadat; Ervin Gubin Moung (2023)“MRI Brain Tumor Detection Methods Using Contourlet Transform Based on Time Adaptive Self-Organizing Map” DOI: 10.1109/ACCESS.2023.3322450, Page(s): 113480 – 113492, 06 October 2023
67. Syed Muhammad Ahmed Hassan Shah; Asad Ullah; Jawaid Iqbal; Sami Bourouis; Syed Sajid Ullah; Saddam Hussain (2023)“Classifying and Localizing Abnormalities in Brain MRI Using Channel Attention Based Semi-Bayesian Ensemble Voting Mechanism and Convolutional Auto-Encoder” DOI: 10.1109/ACCESS.2023.3294562, Page(s): 75528 – 75545, 12 July 2023
68. J. Zhao, Z. Xing, Z. Chen, L. Wan, T. Han, and H. Fu, "Uncertainty-Aware Multi-Dimensional Mutual Learning for Brain and Brain Tumor Segmentation," IEEE J. Biomed. Health Inform., vol. 27, no. 9, pp. 4362–4372, Sep. 2023, doi: 10.1109/JBHI.2023.3274255.